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A Hybrid Model for Pattern Recognition of Marine Turtle Species

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Abstract: Biologists use a manual sea turtle identification key technique to classify marine turtle species according to their scutes patterns. However, limited research to date has focused on developing a system for recognising marine turtle species. Studies in the field of photograph identification system for individual animals have failed to address why none of them developed a system to categorise marine turtle species. The aim of this research is to develop a hybrid model for pattern recognition of marine turtle species based on the stacked generalisation. The hybrid model consists of two major modules: combination unit, which is the combination of the outcomes of neural network model and C4.5 decision tree model, and meta-learning that uses the neural network to aggregate the results from the combination unit and increases the accuracy of the total classification. Several experiments are carried out, where different parameters influencing the overall performance of modules are investigated. The results showed that the trial-error-test could be used to improve the computational cost and mean absolute error of the stacked generalisation when neural networks are used in both combination unit and meta-learning. Therefore, it can be concluded that the hybrid model is an improvement over the traditional manual method for categorization of marine turtle species.

Keywords: C4.5 Decision Tree, Ensemble Classifiers, Marine Turtle Species, Neural Network, Stacked generalisation.

I. Introduction

Sea turtle identification keys are used by biologists to identify marine turtle species (Government, 2007; Laloe, 2015; Marine, 2008; Seaturtle, 1999). The objective of these techniques is to classify marine turtle species using the scutes patterns on the shell (dorsal and ventral view) and top of the head. These techniques are developed according to the existing species in an area. However, limited research to date has focused on developing a system that identifies all marine turtle species independent of their location. Moreover, misclassification of the species can occur when an additional noise appears on the shell. For example, the noise could be seen as an unrecognisable shell because it could be dirty or broken. Interesting was the suggestion made by Lloyd et al. (2012) that a computer system should be developed to identify marine turtle species automatically to increase the classification accuracy of the current methods. To the best of knowledge, there seems to be no system for recognising marine turtle species. Previous research on the photograph identification of individual animals has failed to address why none of them used characteristics of the shell for identifying marine turtle species (Carter et al., 2013; Lloyd et al., 2012; Valdés et al., 2014). A study conducted by Pina et al. (2016) suggested that morphological characteristics, such as colour, shape, and texture, and neural network can be used to develop a model for recognising marine turtle species. Moreover, Carter et al. (2013) demonstrated that neural networks are a strong machine learning algorithm to be used to identify individual turtles. However, studies in the field of pattern recognition have highlighted the issue in generalisation, overfitting, and instability of the neural network (Bataineh, 2015; Zaamout et al. 2012). Also, for the user, it is hard to interpret the meaning of its structure created by weighted links mapping inputs to their outputs. Many techniques were proposed to deal with the weakness of neural networks, such as input pre-processing, modular approach (trial-error-test), ensemble techniques, and genetic algorithm (Kuncheva, 2014; Mitchell, 2002; Zaamout et al., 2012). The genetic algorithm is more adaptable than the others, on the other hand, it is more expensive in terms of time and computational resources (Mitchell, 2002). Theoretical and empirical studies have demonstrated that ensemble techniques can be a strong candidate to mitigate the neural network issues (Kuncheva, 2014). Also, Dietterich (2000) outlined that one of the reasons for why combining classifiers should be implemented is the possibility of insufficient training data. Trainable and untrainable are the two types of ensemble methods (Kuncheva, 2014). Studies in the field of ensemble argued that trainable combiners may lead to better performance improvement (Wang, 2001). An example of a technique that is trainable and uses weighted voting scheme is known as stacked generalisation or stacking (Wolpert, 1992). Studies that applied stacking techniques proved that the results outperform a single classifier achieving considerable classification accuracy in different domain problems (Amini et al., 2015; Vijayan, 2015). However, various methods have been proposed to improve the performance of the stacking. The trial-error-test on the meta-learning or combination unit, and the genetic algorithm to select the suitable data dimensionality, the best ensemble on the combination unit, and to improving the performance of the meta-learning are the most used methods to enhance the performance of the stacking (Ledezma et al., 2010; Moudrik et al., 2015). Although several attempts were made to improve the performance of the stacking, no state-of-the-art research or method can determine the best stacking structure. Because for a given problem domain, the structure should be created accordingly to the characteristics of that problem. However, the mentioned approaches do not consider the use of trial-error-test in both levels of the stacking when the neural network is utilised in both levels.

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The aim of this research is to develop a model for pattern recognition of marine turtle species based on the characteristics of the shell and top of the head. The model is developed using the stacking approach which uses the neural network as meta-learning and in the combination unit. The trial-error-test is employed in both levels of stacking to improve the computational cost and Mean absolute error (MAE) of the hybrid model. Moreover, another model created to classify marine turtle species, based on the sea turtle identification keys, is integrated into the combination unit of the hybrid model to improve its classification accuracy.

II. Input Pre-processing

In this research, different techniques are used to extract the features from marine turtles to create different training sets. First, at the carapace (dorsal view), three morphological characteristics are extracted, such as colour, shape, and texture (Pina et al., 2016). Second, based on the sea turtle identification keys, seven features are extracted using the scutes patterns on the shell and top of the head (Table 1). The training set contains seven marine turtle species and a total of 8064 patterns, 4030, 2561, 253, 236, 495, 235 and 254 for Leatherback, Olive Ridley, Kemp's Ridley, Loggerhead, Hawksbill, Green, and Flatback, respectively. The dataset is created following the Monte Carlos formulation for uniformly distributed random values (Rubinstein et al., 2008). Finally, for the training set created based on sea turtle identification keys some pre-processing filters are applied, such as shuffle the order of the instances and remove duplicates (Table 2) (Pina et al., 2016). Moreover, the data is randomly split into two parts, 75% for training and 25% for testing the generalisation issues of the models (Pina et al., 2016). Weka 3.7 is used to pre-process the raw data, train, and test the models (Hall et al., 2009).

Features	**Description**
The type of carapace	{Hard, Leathery}
The number of costal scutes	Numeric
Overlapping scutes	{yes, no}
Upturned edges	{yes, no}
Round carapace	{yes, no}
The number of prefrontal scutes	Numeric
The number of info-marginal scutes	Numeric

Table 1: Description of the training set based on the sea turtle identification keys.

Features	D_C	D_S	D_T	D_{C+S}	D_{C+T}	D_{S+T}	D_{C+S+T}	D_{IK}
Number of features	20	7	16	27	36	23	43	7
Number of instances	608	507	486	607	602	539	602	1151

Table 2: The properties of the datasets, where $D_{\#}$ is a training set using any feature extracted, C – colour, S – shape, T – texture, and IK – sea turtle identification key (Pina et al., 2016).

III. Proposed approach

The proposed model or hybrid model is based on the stacking technique (Figure 1). The model consists of two major modules: combination unit or level-0, and meta-learning or level-1. In the combination unit, different models, neural network and C4.5 decision tree, are combined.

The goal of the model created by the neural network is to recognise automatically characteristics of the carapace. The model created by C4.5 decision tree is for human interaction, and its goal is to categorise the species based on the scutes patterns on the shell and top of the head. These models share different properties and represent different views on data collection from various perspectives. The meta-learning is trained using the combination of the outcomes of the models on the combination unit, and the features extracted, such as colour, shape, texture, and sea turtle identification keys. This meta-learning is created using a neural network to reduce the errors made by each of the individual models through its training process on the level-0. The neural network was chosen due to its robustness and skills to adjust itself to fit the given data automatically (Zaamout, 2012).

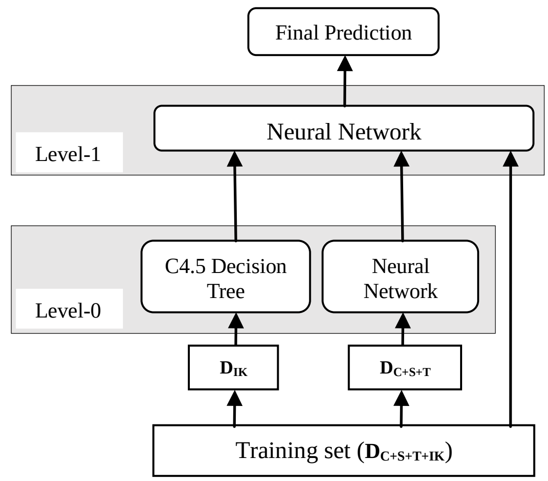

Figure 1: A hybrid model for pattern recognition of marine turtle species.

IV. Experiment setup

In this research, the datasets extracted from the carapace are used to train different neural networks (Pina et al., 2016). A trial-error-test process is conducted using a different number of hidden layers, hidden neurons, different learning rates, training time (epochs), and momentum to determine the "best" neural networks (Table 3). Once the set of "best" networks are determined, the network $*NN_{C+S+T}$ trained using the combination of colour, shape, and texture is used on the combination unit of the stacking. Once the network based on the stacking for automatically recognising carapaces was determined, another model for human interaction was integrated into the combination unit. The aim of this integration is to increase the classification accuracy of the model and keep the computational cost lower. This new paradigm is created based on C4.5 decision tree for identifying the scutes patterns of the marine turtle species based on the sea turtle identification keys. The most popular example of a decision tree using the C.4.5 algorithm is the J48 tree implemented in Weka. Biologists created the sea turtle identification keys according to the existing species in that particular location. Therefore, this model is designed to standardise the sea turtle identification key and is to be used independently of location. C4.5 decision tree is chosen

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because its learning methods are some of the most widely used for inductive inference and to be useful to end users to interpreting the classification problem (Singh, 2014). Furthermore, its simplicity and usability make this approach suitable for this model (Figure 2, and 3). In the end, to reduce the MAE and enhance the computational cost of the hybrid model, the trial-error-test is conducted on the meta-learning.

Networks	Hyper-parameters				ACC (%)
	HL	Epochs	LR	M	
$*NN_C$	a	500	0.3	0.9	99.51
$*NN_S$	a	1000	0.3	0.2	86.19
$*NN_T$	a	900	0.3	0.2	88.89
$*NN_{C+S}$	a	500	0.8	0.2	99.18
$*NN_{C+T}$	a	500	0.9	0.2	99.34
$*NN_{S+T}$	a	500	0.7	0.2	91.47
$*NN_{C+S+T}$	a	500	0.7	0.2	99.00
NN_{C+S+T}	a	500	0.3	0.2	98.34

Table 3: The properties of the best networks according to their hyper-parameters, where $*NN_\#$ is a neural network constructed on any original training set according to Table 2 which applied the trial-error-test, $NN_\#$ is a neural network built on any of the training set according to Table 2, HL – Hidden Layers, LR – Learning rate, M – Momentum, and ACC – Accuracy (Pina et al., 2016).

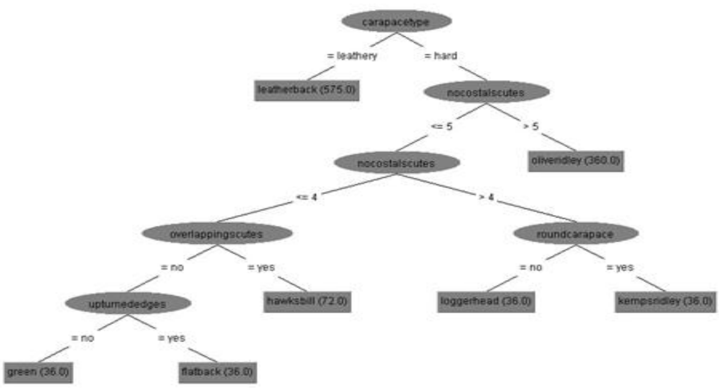

Figure 2: Decision Tree model for pattern recognition of marine turtle species using the scutes patterns.

```
carapacetype = leathery: leatherback (575.0)
carapacetype = hard
|   nocostalscutes <= 5
|   |   nocostalscutes <= 4
|   |   |   overlappingscutes = no
|   |   |   |   upturnededges = no: green (36.0)
|   |   |   |   upturnededges = yes: flatback (36.0)
|   |   |   overlappingscutes = yes: hawksbill (72.0)
|   |   nocostalscutes > 4
|   |   |   roundcarapace = no: loggerhead (36.0)
|   |   |   roundcarapace = yes: kempsridley (36.0)
|   nocostalscutes > 5: oliveridley (360.0)
```

Figure 3: Pruning representation of the decision tree model.

V. Results and Analysis

The modules of hybrid model are handled separately, where several parameters influencing the overall performance of each module are investigated. Table 4 shows the properties of the hybrid model, where ST (#) is a stacking constructed based on any network according to Table 3 on the combination unit and uses the neural network as meta-learning. Results illustrated that overall, the networks had performed well regarding accuracy and generalisation of new images. Both stacking models ST ($*NN_{C+S}$, $*NN_{C+T}$) and ST ($*NN_C$, $*NN_S$, $*NN_T$) achieved maximum accuracy values of 98.5%. However, more investigation along this direction is needed to be done to find the best combination of networks that can reach higher classification accuracy. Regarding computational cost, ST ($*NN_{C+S+T}$) achieved a minimum value of 54 seconds, and ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S}$, $*NN_{C+T}$, $*NN_{S+T}$, $*NN_{C+S+T}$) achieved a maximum value of 479 seconds. It showed that the computational cost increases when the number of networks in the combination unit increases, which confirms with Moudrik et al., (2015). Regarding the MAE, it seems to decrease when a particular number of networks is combined. ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S}$, $*NN_{C+T}$, $*NN_{S+T}$) achieved a minimum MAE value of 0.0151, and ST ($*NN_C$, $*NN_{C+S}$) reached the maximum MAE value of 0.0217. However, the ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S}$, $*NN_{C+T}$, $*NN_{S+T}$) is computationally inefficient. It could mean that choosing stacking network members based on MAE may not be the best way. More investigation needs to be done to find out the best combination. Therefore, the network used on the combination unit of the hybrid model, ST ($*NN_{C+S+T}$), is selected due to its high accuracy rate of 98%, and computationally efficiency of 54 seconds. Also, the combination unit is less complex, and it covers most of the features. Surprisingly, the network ST ($*NN_{C+S+T}$), achieved a minimum MAE value of 0.0167 compared with the networks that reached a maximum accuracy value of 98.5%, ST ($*NN_{C+S}$, $*NN_{C+T}$) obtained a MAE value of 0,0184 and ST ($*NN_C$, $*NN_S$, $*NN_T$) a MAE value of 0.0177. Further experimentation and analysis are required to investigate this observation.

Networks	ACC (%)	MAE	Time (seconds)
ST ($*NN_{C+S+T}$)	98	0.0167	54
ST ($*NN_{C,}$ $*NN_{C+S}$)	98	0.0217	100
ST ($*NN_C$, $*NN_{C+T}$)	98	0.0178	107
ST ($*NN_C$, $*NN_{C+S+T}$)	98	0.0176	109
ST ($*NN_{C+S}$, $*NN_{C+T}$)	98.5	0.0184	117
ST ($*NN_C$, $*NN_{C+S}$, $*NN_{C+T}$)	98	0.0168	156
ST ($*NN_C$, $*NN_S$, $*NN_T$)	98.5	0.0177	249
ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S+T}$)	98	0.0174	334
ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S}$, $*NN_{C+T}$, $*NN_{S+T}$)	98	0.0151	420
ST ($*NN_C$, $*NN_S$, $*NN_T$, $*NN_{C+S}$, $*NN_{C+T}$, $*NN_{S+T}$, $*NN_{C+S+T}$)	98	0.0162	479

Table 4: The properties of the combination unit on the stacking, where ACC - accuracy, and MAE - Mean absolute error.

The results illustrated that the integration of the sea turtle identification key on the combination unit, the hybrid model, which is ST ($*NN_{C+S+T,}$ $J48_{IK}$), increased its success rate, compared with results obtained by Pina et al. (2016) that illustrated that neural networks solely could categorise marine turtle species. Another model, which is ST ($*NN_{C+S+T,}$ NN_{IK}), is developed using neural network based

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on the sea turtle identification key to evaluate the performance of the hybrid model. A trial-error-test process is conducted on the meta-learning to compare the structure of the networks that reduce the MAE and improve the computational efficiency in both hybrid model ST (*$NN_{C+S+T,}$ $J48_{IK}$), and ST (*$NN_{C+S+T,}$ NN_{IK}). It is shown that overall both models performed well achieving the same classification accuracy value of 100%. Moreover, both models achieved a minimum MAE value of 0.0015 (Figure 4: D, F, and H). However, regarding the MAE, ST (*$NN_{C+S+T,}$ NN_{IK}) outperformed the hybrid model when the number of hidden layers was manipulated (Figure 4: B). It could be due to ST (*$NN_{C+S+T,}$ NN_{IK}) which is made of the combination of neural networks, and the number of hidden layers which has a significant effect on neural networks performance (Lahiri et al., 2010). In general, the hybrid model outperformed the ST (*NN_{C+S+T}, NN_{IK}) regarding computational efficiency (Figure 4: A, C, E, and G). It could be because of its diversity in the combination unit, which agrees with Hsu (2012) and Moudrik et al. (2015) that diversity among members, plays a significant role in the success of most ensembles. Moreover, Adeyemo et al. (2015) demonstrated that the C4.5 decision tree outperforms the neural network in the training process. Thus, the decision tree model reduces the time in the training process of the hybrid model. Therefore, this proves that combining similar classifiers can increase the computational complexity, which corroborates with the study of Zhou et al. (2002).

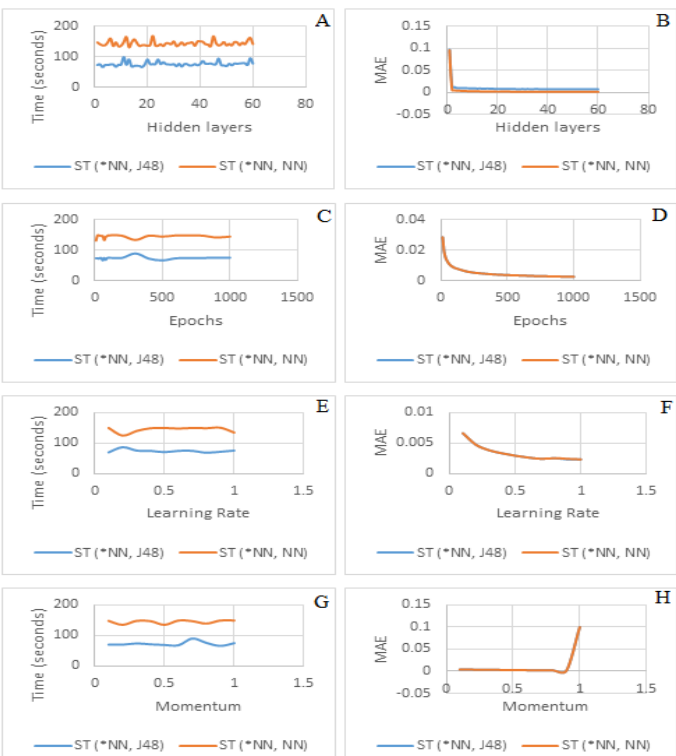

Figure 4: Comparison between the hybrid model ST (*$NN_{C+S+T,}$ $J48_{IK}$) and stacking model of neural networks ST (*NN_{C+S+T}, NN_{IK}).

The hybrid model is compared with the standard stacking technique. The standard stacking uses the network trained with the original training set in the combination unit, ST (NN_{C+S+T}, $J48_{IK}$), and uses the neural network as meta-learning. A trail-error-test is applied on the meta-learning of the ST (NN_{C+S+T}, $J48_{IK}$) to improve its performance. In general, both models, the hybrid model and ST (NN_{C+S+T}, $J48_{IK}$), had the same classification accuracy value of 100% and the same values of MAE (Figure 5: B, D, F, and H). However, regarding computational efficiency, the hybrid model slightly outperformed the ST (NN_{C+S+T}, $J48_{IK}$), 9 seconds of difference, when the momentum was manipulated (Figure 5: G). It can be inferred that applying trial-error-test in both levels of the stacking when the neural network is present in both levels, the computational cost and the MAE decrease. However, more experiments are required to investigate this observation, whether this is true on different training sets related to other domain problems. Other trainable combiners are used to compare their results according to the hybrid model (Table 5). It is shown that several ensemble methods could be used to increase the classification accuracy of the neural network. In general, all the techniques were able to generalise the new images. AdaBoost outperformed all models by a computational cost of 8 seconds. Bagging achieved a higher computational cost of 183 seconds compared with all models. Unlike the Bagging and AdaBoost approaches which only combine the same type classifiers, the stacking approach can be used to combine several types of classifiers through meta-learning to maximise the generalisation accuracy (Kuncheva, 2014). However, the hybrid model and ST (NN_{C+S+T}, $J48_{IK}$) achieved the minimum MAE value of 0.0015 compared with the other techniques.

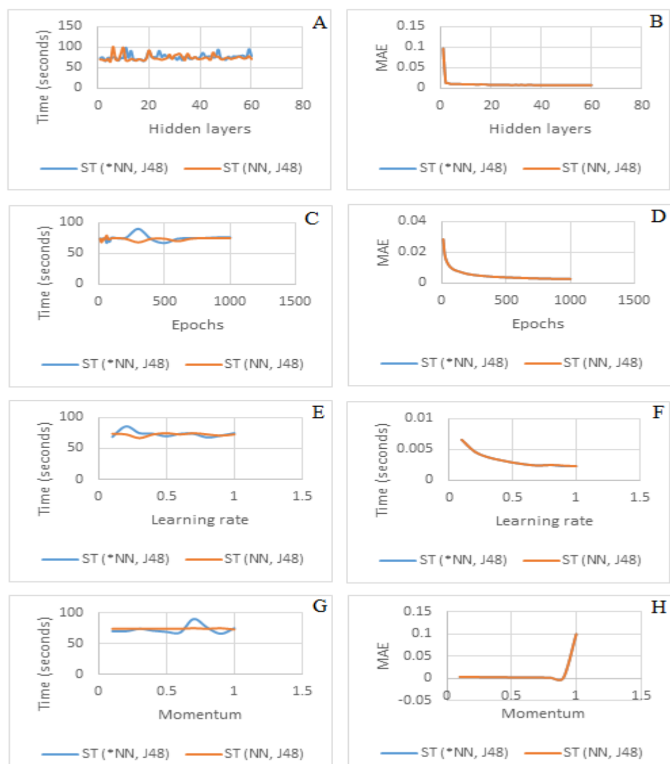

Figure 5: Comparison between the hybrid model ST (*$NN_{C+S+T,}$ $J48_{IK}$) and stacking model trained using an original training set ST (NN_{C+S+T}, $J48_{IK}$).

Ensembles	HP				ACC (%)	MAE	T
	HL	EP	LR	M			
AdaBoost	-	-	-	-	100	0.0026	8
Bagging	-	-	-	-	100	0.0025	183
ST (NN_{C+S+T}, $J48_{IK}$)	-	-	-	-	100	0.0099	78
ST (*NN_{C+S+T}, $J48_{IK}$)	-	-	-	-	100	0.0099	78
ST (NN_{C+S+T}, $J48_{IK}$)	a	500	0.3	0.9	100	0.0015	75
Hybrid model	**a**	**500**	**0.3**	**0.9**	**100**	**0.0015**	**66**

Table 5: Comparison between the hybrid model and trainable ensemble, where HP - Hyperparameters of the meta-learning, HL - Hidden Layers, EP - Epoch, LR - Learning rate, M - Momentum, ACC - Accuracy, MAE - Mean absolute error, and T - Time (seconds).

VI. Conclusion

The results clearly show that the model can be used to recognise patterns of marine turtle species. The integration of the sea turtle identification key on the combination unit enhanced the performance of the hybrid model regarding training time and classification accuracy. Moreover, applying the trial-error-test in both levels of the stacking slightly improved its computational cost and reduced the value of MAE. However, more accurate conclusions will be possible when this approach will be applied to different training sets belonging to other domain problems. The hybrid model will be used to support biologists in identifying the species of marine turtles even when noise is present in the images. Also, this model will be utilised as an educational tool so that the communities who would not have any prior knowledge about the marine turtle species could categorise them. Therefore, fewer experts are needed, and more communities are involved in the conservation of these species. For future works, the genetic algorithm should be used on both levels of the hybrid model to find the suitable structure, hyper-parameters of the neural networks and to increase the performance of the model. Also, more models should be trained using more features extracted from the marine turtle species, such as facial profile, size, claws, and crawl (tracks and other signs left on a beach). Moreover, these models should be integrated into the hybrid model to make a very efficient model.

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